A Process For The Creation Of Fuzzy Cognitive Maps from Monte Carlo Simulation Generated Meta Model

CROSS-REFERENCE TO RELATED APPLICATIONS

This is a continuation of U.S. provisional application 60/420,928,

filed on October 24, 2002.

BACKGROUND

This invention relates to a process for generating fuzzy cognitive maps from a Monte Carlo simulation-generated Meta Model. Using this invention, one can identify variables that have a positive or negative correlation with a phenomenon. This invention also aids in improving phenomena by moving correlating variables towards targets.

It is difficult to identify those factors that have a significant contribution to the outcome of a phenomenon, a phenomenon such as Apartheid South African politics (see Fig. 7), the behavior of an axle on a car, or the failure of a containment vessel in a nuclear reactor. In the present invention, Applicant uses a process to identify those factors that have a significant contribution to the behavior of a phenomenon by using a computer to create a fuzzy cognitive map (FCM).

A fuzzy cognitive map (FCM), is a graph of an event, function, or process that shows the factors or concepts involved in the event, function, or process, and how those factors/concepts influence each other to create a phenomenon. The FCM includes all the factors or concepts that cause or influence the event, function, or process, and the relationships between the factors/concepts. FCMs have historically been drawn by hand by individual experts based on their knowledge of and experience with the event, function, or process. Using this invention, one can use a computer to generate a FCM.

An example of these factors/concepts can be seen in Fig. 7, which is a fuzzy cognitive map of Apartheid South African politics. In Fig. 7 a short description of each factor is enclosed in an ellipse. The relationships of these factors are shown as arrows connecting the factors. The arrows have a direction and a value between +1 and -1.

1

The value of the number indicates the influence (or causality) of one factor/concept on another factor/concept:

- A value > 0 means that there is a positive influence or causality (when a factor/concept increases then another factor/concept will increase).

- A value < 0 means that there is a negative influence or causality (when a factor/concept increases then another factor/concept decreases).

A computer generated FCM is created from a Meta Model generated from Monte Carlo simulations. A Monte Carlo simulation randomly selects the values for the input variables. Monte Carlo is a random number generation process similar to rolling dice or flipping a coin. These Meta Models create a finite, non-redundant *set of rules* that state "if A then B, with probability P." A and B are factors or concepts in the model with P being the direction and magnitude of the arrow showing the influence or causality of A on B.

A meta-model, described in Marczik, J. Principals of Simulation-Based Computer-Aided Engineering, FIM Publications, Barcelona, September 1999 (herein incorporated by reference), page 47, is a stacked matrix consisting of all the inputs and all the outputs from a Monte Carlo simulation. The matrix has a row for each Monte Carlo sample and columns for each input and output that goes into the simulation. Using a Monte Carlo simulation, one can take variability and uncertainty into account for every input variable in a problem. Each Monte Carlo run will have different values for the input variables in an analysis. The value of each input variable is randomly selected from all the values within a range of potential values for that variable. A simulation can have any number of variables. Generally, the more variables that one includes, the more realistic the simulation will be.

The outputs of the Monte Carlo runs are different values as each Monte Carlo run has different inputs. Fifty to one hundred Monte Carlo samples are sufficient to obtain useful statistical information on the outputs.

The Monte Carlo method is independent of the problem being simulated. Each run using Monte Carlo is one analysis of that particular problem, event, function, or process. Each particular type of problem, event, function, or process is analyzed using an equation known as a solver. The process being described is independent of the field of application, however for the process to work the field of application has to have solvers that are known to be accurate in modeling reality.

While FCMs have been applied in fields as diverse as politics, economics, medicine, and history; the automatic generation of FCMs using this process is limited to those fields that have accurate solvers (formulas that accurately show interactions). The science and engineering fields are the most likely initial applications for this process. In the present invention, when the terms equation or equations are used, we are referring to solvers.

SUMMARY

The present invention is a process for the generation of fuzzy cognitive maps from Monte Carlo simulation-generated Meta Models that identify variables that have a positive or negative correlation with a phenomenon. This invention also aids in improving phenomena by moving correlating variables towards targets.

DRAWING FIGURES

In the drawings, closely related figures have the same number, but different alphabetic suffixes.

Figs. 1A and 1B show a single process overview flow diagram that is connected at 21.

Fig. 2 is a flow diagram that shows the process for generating a base matrix.

Fig. 3 shows two input variables with one output variable base matrix.

Figs. 4A, 4B, 4C and 4D are a flow diagram that shows the process for expanding a Meta Model. The flow diagram is connected at 131, 129, 127, 125, 123, 113, 115, 117, 119, 121, 149, 151, and 187.

Fig. 5 shows an expanded Meta Model.

Figs. 6A, 6B, and 6C are a flow diagram that shows the process for improving a Meta Model. The flow diagram is connected at 233, 235, 237, 245 and 247.

Fig. 7 shows a Fuzzy Cognitive Map (FCM) representing politics in Apartheid South Africa.

Detailed Description of the Preferred Embodiment

An overview of the process for generating fuzzy cognitive maps and desirable value ranges for input variables can be found in the flow diagrams in figures 1A and 1B (joined at 21).

In fig. 1A, one can see the prerequisites for the first step of the process of creating a Meta Model. First, an equation or set of equations is selected **1** (fig 1A) to model a phenomenon. Let's select, as an example, the simulation of the force on an object. It is known that the force is equal to the mass of the object, m, times the acceleration of the object, a, or F=ma. Next, the logical mean for each input variable is selected **3**. In this example, limiting our selection to integers, we will assume that the mean of the mass variable is 5 units and the mean of the acceleration is 10 units. The logical range for each input variable is then selected **5**. In this example the range for mass can vary from 4 to 6; the range for mass is plus or minus 1 unit from the mean. The acceleration can vary from 8 to 12 units; the range is plus or minus 2 units from the mean of 10 **5**. At this time we must decide on the number of trials N that must be run **7**. We must also count the number of input variables M **9** and the number of outputs V **11**; in our example the number of input variables are two and the number of outputs is one. Next, one selects the logical distribution function, such as a normal distribution **15**, or any other type of distribution equation that approximates the distribution that is generated by experimentation or by extrapolation from experience.

Creating a base matrix (17)

Figure 2 shows the process for generating a base matrix. The process for creating a base matrix begins by initializing variables (see steps **45, 53,** and **55** in fig 2). One also creates an empty matrix with the number of columns equal to the number of input variables plus the number of output variables **47**. One then populates the empty matrix created in step **47**, row by row, with input variable values, within each input variable's specified range, as generated random numbers that conform to the desired distribution function for that input variable **61** and are placed in the input variable's cell **63**. When all input values are generated in a row (see **59** and **65**), one calculates the solution to each equation **67** using the input values generated at step **61** and stores each value in the appropriate cell **69**. This process continues until all equations are solved (see steps **71** and **57**). After an entire row of the base matrix has been populated, the generated row is stored in the relevant row of the base matrix **69**. This process is repeated for the remaining rows (see **73** and **49**) until the base matrix is totally populated. The base matrix is then stored **75**. The generated base matrix **78** for our two input variables and one output variable can be found in Fig. 3.

Each row **51** of the base matrix **78** represents one trial. The first two columns **50** and **48** are the generated input values for the input variables. The last column **46** contains all output values.

In our example, the numbers in the base matrix for ten trials are:

m	a	F
5	10	50
5	11	55
4	10	40
5	8	40
6	9	56
5	12	60
5	10	50
6	9	54
4	11	44
5	8	40

This Base matrix of an actual problem will be much larger, with n input variables (x1, x2, x3, x4, ..., xn) and m outputs (y1, y2, y3, ..., ym) and N Monte Carlo samples with N usually being from 50 to 100. The base matrix can be graphically viewed from any combination of 2 or 3 inputs and outputs with each view having N points.

Expanding the Meta Model (Fig. 1B 25)

Figs. 4A, 4B, 4C and 4D show the process for expanding the Meta Model. One expands the Meta Model by first selecting the number of expansions or perturbations T that will be required {see fig 1A **13**). Next, one selects the number of trials for the expanded Meta Model (Fig. 1B **23**). Then one selects fuzzy levels for the solutions to the equations (Fig.1A **19**). These fuzzy levels represent a region of the solution space of an equation, demarcated by fuzzy level boundaries, whose members have at least one common characteristic. One typically calls one region high and another region low, but the number of fuzzy levels one could create can be more than three. One could create a Meta Model with 5 fuzzy levels, i.e., the base matrix, very low, low, high, and very high.

A Meta Model with three defined fuzzy levels can be seen in Fig. 5 with the base matrix **78** generated in the first stage of the process wedged between the values that have a high values **209** (fuzzy level) and low values **205** (fuzzy level).

In most instances, one perturbation will be sufficient to create an expanded Meta Model. Next, values will be initialized (see Fig. 4A **85, 89, 91** and **93**). Next, the values of a single input variable in a single column (see example columns **48** or **50** in Figs. 3 and 5) are incremented by a fixed value **99** and the output value of an equation is calculated **103**. This output value of the equation is then stored in the matrix **105**. Has the output value jumped to another fuzzy level **153**? If the value does jump to another fuzzy level **153** and if the solution to the equation jumps to a higher value fuzzy level **189**, then that input variable has a positive correlation **197**. If the output value jumps to a lower fuzzy level then the output variable has a negative correlation **191**. If the increase in the input variable value does not result in a jump to another level of the output value, the non-incremented value is decremented **155** and the output value of one of the equations is recalculated **157** and retested (see **159** and **161**). If the decremented input value jumps to a higher fuzzy level then that input variable has a negative correlation **163**. If the value jumps to a lower fuzzy level, then that input variable has a positive correlation **169**. If there is no change in levels, the variable is non-responsive **171**.

This testing for a correlation is repeated for each trial of a given variable (see **97, 165, 167, 193, 195** and **173**). Once an entire column representing a given input variable is tested, one counts the number of trials that have positive and negative correlation's. These counts of the number of positive and negative correlation's are counted and the count numbers are divided by the total number of trials to get positive (p+) and negative (p-)**107**. Then the generated matrix **109** and a copy of the generated matrix are stored **111**. This process continues for each equation (see **101** and **175**) and for each of the remaining input variables (see **95** and **137**).

This cycle for building this Meta Model can be repeated T times (see Fig 1A **13, 87, 133,** and **135**) to gain insights into the dynamic relationships between the various factors (input variables) and a phenomenon.

Process of Generating a FCM From A Meta Model

The inputs and outputs contained in the Meta Model are the factors/concepts contained in the FCM (the A's and B's in the set of rules that state "if A then B, with probability P"). The results of expanding the Meta Model **39** supply the information required to generate a fuzzy cognitive map **41**.

Using Meta Models, causal links have now been identified that show how all the input variables influence the output variables in the presence of variation. The set of rules created by expanding the Meta Model are used to create a FCM in which all the input variables (A's) and output variables (B's) are the factors or concepts involved in an event, function, or process. The relationships between the factors/concepts are provided by the sign of the causal link (positive or negative) and the probability P.

In our example, an increase in the level of input variable x1 (mass m) will result in an increase of output y1 (force F). An increase in the level of input variable x2 (acceleration a) will also result in an increase of output y1 (force F). In our example, the relationships between the input variables and the output variable will be positive with probabilities of 1.

When a computer program generates a FCM from the data generated by expanding the Meta Model, the diagram (see Fig. 7), it will map the relationship between an input variable and a phenomenon (output) that has the highest probability, with the arrows directed from the input variable to the phenomenon (output). For example, in the FCM of the Apartheid South African politics (Fig. 7), if White Racist Radicalism **293** has a .72 positive correlation for producing a National Party Constituency **298** and there is a .06 negative correlation between White Racist Radicalism **293** and a National Party Constituency, what is displayed on a FCM is **302** — a .72 positive correlation (see also Kosko, B., Neural Networks and Fuzzy Systems, Prentice Hall International Editions, 1992, herein incorporated by reference).

In Fig. 7, there are a number of notable correlation's. For example, there is a very strong .98 positive relationship **303** between Foreign Investment **292** and the Strength of Government **296**, a very strong .92 positive relationship between Foreign Investment **292** and Mining **294** (see **302**), a very strong .92 positive relationship between Foreign Investment **292** and Black Employment **300** (see **301**) and there is a moderately strong .56 negative relationship between Black Employment **300** and Black Tribal Unity **299** (see **304**).

The National Party Constituency 298 has no effect on the Job Reservation Law 297 (see relationship 305). Other factors that influence and were influenced within Apartheid South African politics include Apartheid 295 and White Racist Radicalism 293.

Manipulating a Fuzzy Cognitive Map (FCM)

One can generate an improved Meta Model 33 by moving the Meta Model. The Meta Model is moved to get improved outputs, such as reduced weight or cost while maintaining the ability of the product to perform. A new FCM is then built from the new Meta Model using the process previously described.

The first steps in the process to improve the output of the Meta Model (see Fig. 6A, 6B and 6C), are to create an empty base/data matrix 215, to create an empty in_matrix for running value comparison tests 213 and to perform a number of initializations see 211, 223, 229, and 231. Also, one needs to select at least one target solution to an equation or target solutions to a number of equations and place the target solutions in an array 217. One also selects means and ranges for each input variable 219 and store said means and ranges in a Dstart and Vval matrix 221. The process is similar to creating a base matrix. One begins by using a Monte Carlo simulation to generate random numbers of all input variables for a trial (see steps 277, 283, 285 and 289). Then, using the generated input variable values, a solution for one of the equations is calculated 279 and stored in a variable Vval 281 and in the output variable cell for a trial n in the in_matrix and in the base/data matrix 287. This process is repeated for each trial (see steps 291 and 249) and the generated values are stored in a matrix 251. All the generated output values are compared with the target value and the closest solution to the target value is selected 253 and the trial n of this closest solution is stored 255. If the absolute value of the difference between the closest solution and the target solution is less than prior cycles 259 then the new values are placed in the in_matrix and designated the closest input values 263. These closest input values are substituted for existing means in the Vval matrix 267 and stored in the in_matrix 269. This process is cycled over and over again until there is no decrease in the absolute value of the output compared to prior cycles (see 259 and 271). Once this happens, the next equation with a target value (see 238 and 242) is tested (see 257, 261 and 265). This process is repeated until all target values have been improved see 225 and 227.

Accordingly, one can see that by using the present invention one can use a computer to easily generate a Fuzzy Cognitive Map. This is a marked improvement over the existing hand drawn Fuzzy Cognitive Maps. Any phenomenon that can be described or modeled by an equation or a set of equations can be analyzed through a computer generated Fuzzy Cognitive Map. Moreover, the gradation of analysis of a phenomenon can be increased or decreased by increasing or decreasing the number of fuzzy levels.

Thus the scope of this invention should be determined by the appended claims and their legal equivalents, rather than by any example given in this document.